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Artificial neural networks for modelling the mechanical properties of steels in various applications

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Abstract

The application of artificial neural networks (ANNs) in predicting some key properties of steels is discussed in detail. This paper reports on the effectiveness of three back-propagation artificial neural network models that predict (i) the impact toughness of quenched and tempered pressure vessel steel exposed to multiple postweld heat treatment (PWHT) cycles, (ii) the hardness of the simulated heat affected zone in pipeline and tap fitting steels after in-service welding and (iii) the hot ductility and hot strength of various microalloyed steels over the temperature range for strand or slab straightening in the continuous casting process. Predicted and actual experimental values for each model are well matched and highlight the success of applying ANNs in predicting mechanical properties. The capability of ANNs in predicting multiple outputs (hot ductility and hot strength) is also demonstrated.

The sensitivity, which is a measure of the response of an output across the range of an individual input variable, of key input variables (individual alloys and/or process steps) for each model is shown to be in agreement with findings of both the experimental investigation and reports in the literature. Although this paper shows that ANNs can be employed for optimizing steel and process design parameters, some difficulty can arise when inter-relationships exist between input variables. An understanding of the inter-relationships between input variables is essential for interpreting the sensitivity data and optimizing design parameters. It is argued that artificial neural network models can be developed that have the capacity to eliminate the need for expensive experimental investigation in areas, such as welding (new and repair), inspection and testing, and manufacturing processes.

Keywords: Artificial neural network modelling; Steels; Impact toughness; Hardness; Hot ductility; Continuous casting; In-service welding

1. Introduction

Artificial neural networks (ANNs) are computational networks that attempt to simulate the processes that occur in the human brain and nervous system during pattern recognition, information filtering and functional control [1]. Alter [2] describes ANNs as systems that recognize patterns based on the data used to train them, where each training case is characterized by a set of inputs and a result (output or multiple outputs). The use of these networks to make predictions of the mechanical properties of materials is a relatively new concept, but one that has received considerable interest in recent years. ANNs have been reported to be very effective in analysing the tensile properties of welds in power plant steels [3], the effect of carbon content on the hot strength of steels [4] and the impact toughness of welds based on common welding parameters [5].

This paper introduces three different back-propagation neural network models which can predict the (i) impact toughness of quenched and tempered steels exposed to various postweld heat treatment (PWHT) cycles, (ii) simulated heat affected zone toughness of pipeline steels resulting from in-service welding and (iii) hot ductility (reduction of area (ROA)) and hot tensile strength of microalloyed steels. A back-propagation neural network is the most common type of neural network and it undergoes its learning phase by calculating an error between the predicted and actual output. This ANN incorporates a hidden layer that is used to establish the inter-relationships between the input variables and their rela-

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tionship with the output to minimize the error between the actual and predicted output.

The testing of QT steels to qualify them for pressure vessel use is a time consuming and expensive process. Hence, the development of a reliable model to predict relevant mechanical properties, such as impact toughness as a function of alloy content (steel design) and heat treatment conditions (process parameters), is a worthwhile goal for the pressure vessel industry. Modelling impact toughness can be difficult due to the well-known scatter that is associated with Charpy V notch impact testing. However, ANNs automate the modelling process and this improves the possibility of success.

Accurate prediction of hardness of the heat affected zone of a weldment as a function of composition and cooling time can make a valuable contribution to the avoidance of crack-prone microstructures during in-service welding. The second model presented in this paper demonstrates the accuracy with which hardness values can be predicted in simulated HAZ structures, which in turn can be used to avoid crack-prone structures (>350 HV). This neural network model incorporates materials characteristics (chemical composition and as-received hardness), peak temperature, holding time and cooling rate as key input variables for predicting hardness.

The third model predicts hot ductility and hot strength of microalloyed steels based on chemical composition and treatment conditions. The purpose of this model is to assess the likelihood of steels developing transverse cracking during the straightening operation in the continuous casting process. This model is designed to predict two outputs, and in doing so it provides an insight of the functional behaviour of artificial neural networks in cases of multiple outputs.

As well as predicting specific mechanical properties as a function of process and material parameters, all three models allow the optimization of these parameters through a sensitivity analysis of the input variables. Sensitivity is a measure of the response of output across the entire range of an individual input variable [6]. In short, the aim of this paper is to underline the usefulness and effectiveness of artificial neural networks to predict, with relatively high accuracy, various properties of steels and discuss the advantages and limitations of ANNs in steel and process design.

2. Experimental methods

2.1. Artificial neural network modelling

Neuralworks Professional II/Plus Software was used to build the three back-propagation neural networks. As mentioned, the models were designed to predict the: (i) impact toughness of quenched and tempered steels exposed to repeated PWHT cycles (Model 1), (ii) simulated HAZ hardness of pipeline and tap fitting steels after in-service welding (Model 2) and (iii) reduction of area (hot ductility) and hot

Table 1
Input variable data ranges used for the three models

Input variable	Model 1		Model 2		Model 3	
	Minimum value	Maximum value	Minimum value	Maximum value	Minimum value	Maximum value
Thickness (mm)	11	20				
Test type[a]	T	L			M	S
Test temperature	−90	20			700	1100
Time[b]	0	200	0	2		
Cooling[c]	Slow	Fast	2	10	100	200
Normalised HV			159	234		
%C	0.155	0.180	0.07	0.29	0.155	0.165
%Mn	1.10	1.43	0.44	1.63	0.63	1.23
%S	0.0020	0.0035	0.005	0.024		
%Cr	0.016	0.2	0.012	0.31		
%B	0.0005	0.0013				
%Si			0.005	0.39		
%Cu			0.010	0.28		
%Ni			0.009	0.1		
%Mo			0.005	0.033		
%V			0.005	0.06		
%P			0.008	0.02		
%Ti			0.005	0.021	0.003	0.018
%Al			0.005	0.039	0.027	0.036
%Nb			0.005	0.053	0.001	0.022
%N					0.0021	0.0033

[a] 'T' denotes the direction of rolling is transverse to the length of Charpy sample, 'L' denotes the direction of rolling is longitudinal to the length of Charpy sample, 'M' denotes the samples were melted and solidified in situ to simulate direct casting conditions and 'S' denotes the samples were solution treated to simulate re-heated conventional type cast structures.

[b] In Model 1 'time' is PWHT time (min) and in Model 2 time is holding time (s) at 1400 °C.

[c] In Model 1 'slow' is cooling from 570 °C at 250 °C/h to 400 °C and then still air, 'fast' cooling is cooling in still air from 570 °C. In Model 2 'cooling' is $t_{8/5}$ cooling time (s) and in Model 3 cooling is the cooling rate (°C/min) of the samples.